

# Conventions, Accuracy Metrics, Classification, Regression

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# Outline

1. Introduction and Demos
2. Machine Learning Fundamentals
3. First ML Example: Tomato Quality Prediction
4. Classification vs Regression
5. Classification Metrics
6. Regression Metrics
7. Data Visualization and Baselines
8. Summary and Key Takeaways

# Demo

- Complete PoseNet Demo

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- [Complete PoseNet Demo](#)
- [Blog post from Google](#)

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- [Complete PoseNet Demo](#)
- [Blog post from Google](#)
- [Rock Paper Scissors](#)

# Revision: What is Machine Learning

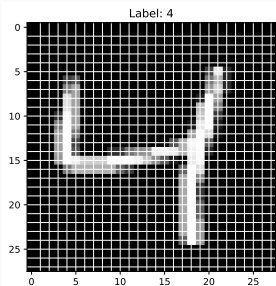
“Field of study that gives computers the ability to learn without being explicitly programmed” - Arthur Samuel [1959]

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Let us work on the digit recognition problem.

**Notebook:** rule-based-vs-ml.html



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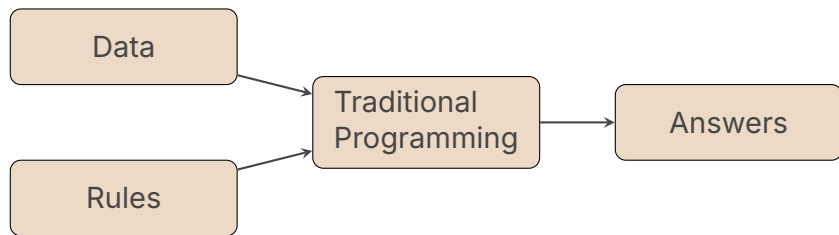
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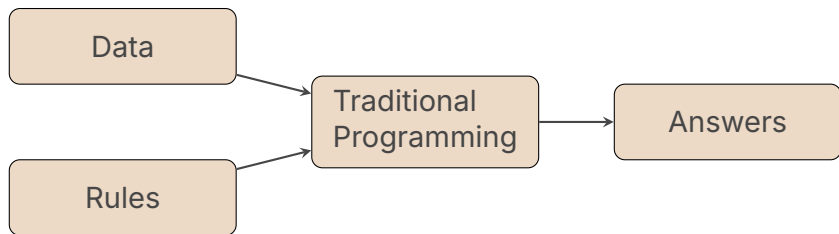
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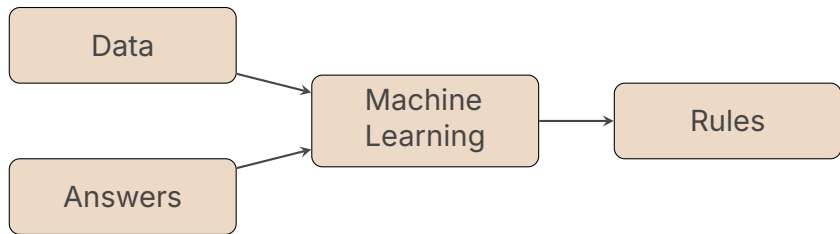
# Traditional Programming vs Machine Learning



# Traditional Programming



# Machine Learning



# Revision: What is Machine Learning

"A computer program is said to learn from experience  $E$  with respect to some class of tasks  $T$  and performance measure  $P$  if its performance at tasks in  $T$ , as measured by  $P$ , improves with experience  $E$ ." - Tom Mitchell

# Pop Quiz #1

## Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction



## Pop Quiz #2

### Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction
- b) Size of a house for price prediction

## Pop Quiz #3

### Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction
- b) Size of a house for price prediction
- c) Sample ID number

# Pop Quiz #4

## Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction
- b) Size of a house for price prediction
- c) Sample ID number
- d) Age for medical diagnosis

# Pop Quiz #5

## Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction
- b) Size of a house for price prediction
- c) Sample ID number
- d) Age for medical diagnosis

# Pop Quiz #6

## Quick Question!

In machine learning, which of the following is typically NOT a useful feature?

- a) Color of a tomato for quality prediction
- b) Size of a house for price prediction
- c) Sample ID number
- d) Age for medical diagnosis

**Answer:** c) Sample ID numbers are arbitrary identifiers, not meaningful features!

# First ML Task: Grocery Store Tomato Quality Prediction

Problem statement: You want to predict the quality of a tomato given its visual features.

# Dataset

Imagine you have some past data on quality of tomatoes.  
What visual features do you think will be useful?

# Dataset

Imagine you have some past data on quality of tomatoes.  
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Imagine you have some past data on quality of tomatoes.  
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- Size
- Colour

# Dataset

Imagine you have some past data on quality of tomatoes.  
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# Dataset

Imagine you have some past data on quality of tomatoes.  
What visual features do you think will be useful?

- Size
- Colour
- Texture

# Sample Dataset

Here is our example dataset with tomato features:

<b>Sample</b>	<b>Colour</b>	<b>Size</b>	<b>Texture</b>	<b>Condition</b>
1	Orange	Small	Smooth	Good
2	Red	Small	Rough	Good
3	Orange	Medium	Smooth	Bad
4	Yellow	Large	Smooth	Bad

# Useful Features

Is the sample number a useful feature for predicting quality of a tomato?

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Let us modify our data table for now.

Colour	Size	Texture	Condition
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad

# Training Set

<b>Colour</b>	<b>Size</b>	<b>Texture</b>	<b>Condition</b>
Orange	Small	Smooth	Good
Red	Small	Rough	Good
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The training set consists of two parts:

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1. Features (Input Variables)

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The training set consists of two parts:

1. Features (Input Variables)
2. Output or Response Variable

# Training Set

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Orange	Small	Smooth	Good
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We call this matrix as  $\mathcal{D}$ , containing:

1. Feature matrix ( $\mathbf{X} \in \mathbb{R}^{n \times d}$ ) containing data of  $n$  samples each of which is  $d$  dimensional.

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1. Feature matrix ( $\mathbf{X} \in \mathbb{R}^{n \times d}$ ) containing data of  $n$  samples each of which is  $d$  dimensional.
2. Output vector ( $\mathbf{y} \in \mathbb{R}^n$ ) containing output variable for  $n$  samples.

# Data Matrix Details

- Feature matrix:  $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1^\top \\ \mathbf{x}_2^\top \\ \vdots \\ \mathbf{x}_n^\top \end{bmatrix}$  where  $\mathbf{x}_i \in \mathbb{R}^d$

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- Example (after encoding):  $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$  (Orange=1, Small=0, Smooth=1)
- Complete dataset:  $\mathcal{D} = \{(\mathbf{x}_i^\top, y_i)\}_{i=1}^n$



# Prediction Task

Estimate condition for unseen tomatoes (#5, 6) based on data set.

<b>Colour</b>	<b>Size</b>	<b>Texture</b>	<b>Condition</b>
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad
Red	Large	Rough	?
Orange	Large	Rough	?

# Testing Set

Testing set is similar to training set, but, does not contain labels for output variable.

Colour	Size	Texture	Condition
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad
Red	Large	Rough	?
Orange	Large	Rough	?

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# Prediction Task

We hope to:

1. Learn  $f$ : Condition =  $f(\text{colour, size, texture})$
2. From Training Dataset
3. To Predict the condition for the Testing set

Colour	Size	Texture	Condition
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad
Red	Large	Rough	?
Orange	Large	Rough	?

# Generalisation

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# Generalisation

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# Generalisation

- Q: Is predicting on test set enough to say our model generalises?
- A: Ideally, no!
- Ideally - we want to predict "well" on all possible inputs. But, can we test that?
- No! Since, the test set is only a sample from all possible inputs.

# Generalisation

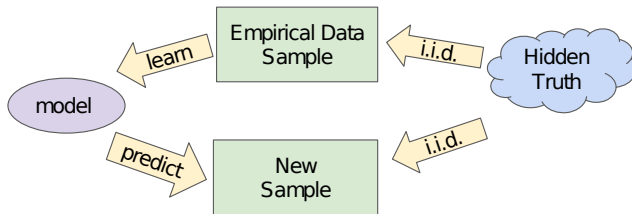


Image courtesy Google ML crash course

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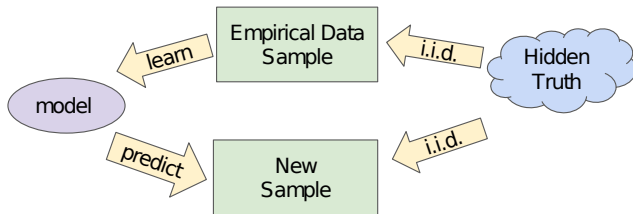


Image courtesy Google ML crash course

Both the training set and the test set are samples drawn from the hidden true distribution (also sometimes called population)

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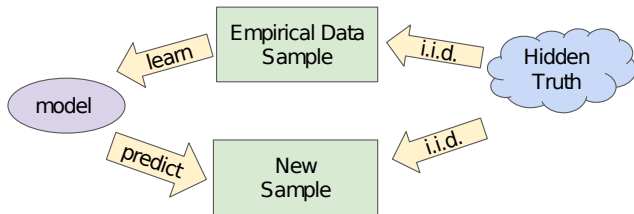


Image courtesy Google ML crash course

Both the training set and the test set are samples drawn from the hidden true distribution (also sometimes called population)

More discussion later once we study bias and variance

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Question: What factors does the campus energy consumption depend on?

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Answer:

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Question: What factors does the campus energy consumption depend on?

Answer:

- # People (More people  $\implies$  More Energy)
- Temperature (Higher Temp.  $\implies$  Higher Energy)

# People	Temp (C)	Energy (kWh)
4000	30	30
4200	30	32
4200	35	40
3000	20	?
1000	45	?

## Pop Quiz #7

### Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not

# Pop Quiz #8

## Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not
- b) Classifying images as cat, dog, or bird

# Pop Quiz #9

## Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not
- b) Classifying images as cat, dog, or bird
- c) Predicting house prices

# Pop Quiz #10

## Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not
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- c) Predicting house prices
- d) Determining if a tumor is malignant or benign

# Pop Quiz #11

## Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not
- b) Classifying images as cat, dog, or bird
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# Pop Quiz #12

## Quick Question!

Which of these is a regression problem?

- a) Predicting if an email is spam or not
- b) Classifying images as cat, dog, or bird
- c) Predicting house prices
- d) Determining if a tumor is malignant or benign

**Answer:** c) House prices are continuous values - that's regression!



# Classification vs Regression

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  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)

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  - i.e.  $y_i \in \mathbb{R}$
  - Examples - Predicting:
    - How much energy will campus consume?
    - How much rainfall will fall?



# Metrics for Classification

Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
Good	Good
Good	Good
Good	Bad
Good	Bad
Bad	Bad

Ground Truth: From the actual training set

Prediction: Made by the model

# Accuracy

Prediction ( $\hat{y}$ )

✓	Good
✓	Good
	Good
	Good
✓	Bad

Ground Truth ( $y$ )

Good
Good
Bad
Bad
Bad

# Accuracy

	Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
✓	Good	Good
✓	Good	Good
	Good	Bad
	Good	Bad
✓	Bad	Bad

$$\begin{aligned}\text{Accuracy} &= \frac{|\{i : y_i = \hat{y}_i\}|}{n} \\ &= \frac{3}{5} = 0.6\end{aligned}$$

# Mathematical Notation: Set Cardinality and Indicator Functions

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  - Counts how many samples satisfy the condition
- **Alternative: Indicator function notation**

$$\text{Accuracy} = \frac{\sum_{i=1}^n \mathbf{1}[y_i = \hat{y}_i]}{n}$$

$$\text{where } \mathbf{1}[\text{condition}] = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$$

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- Both notations are mathematically equivalent and commonly used in ML literature

# Types of Data: Imbalanced Classes

1 sample {  
100 samples {  $\begin{pmatrix} \text{Bad} \\ \text{Good} \\ \text{Good} \\ \dots \\ \text{Good} \end{pmatrix}$  Imbalanced Classes

# Types of Data: Imbalanced Classes

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Cases for this:

- Cancer Screening

# Types of Data: Imbalanced Classes

$$\begin{array}{l} 1 \text{ sample} \{ \\ 100 \text{ samples} \{ \end{array} \left( \begin{array}{c} \text{Bad} \\ \text{Good} \\ \text{Good} \\ \dots \\ \text{Good} \end{array} \right) \quad \text{Imbalanced Classes}$$

Cases for this:

- Cancer Screening
- Planet Detection

# Accuracy Metrics: Precision

	Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
→ ✓	Good	Good
→ ✓	Good	Good
→	Good	Bad
→	Good	Bad
	Bad	Good

$$\text{Precision} = \frac{|\{i : y_i = \hat{y}_i = \text{Good}\}|}{|\{i : \hat{y}_i = \text{Good}\}|} = \frac{2}{4} = 0.5$$

“the fraction of relevant instances among the retrieved instances”, i.e. “out of the number of times we predict Good, how many times is the condition actually Good”



# Accuracy Metrics: Precision

	Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
→ ✓	Good	Good
→ ✓	Good	Good
→	Good	Bad
→	Good	Bad
	Bad	Good

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"the fraction of relevant instances among the retrieved instances", i.e. "out of the number of times we predict Good, how many times is the condition actually Good"

# Accuracy Metrics: Recall

	Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
→ ✓	Good	Good
→ ✓	Good	Good
	Good	Bad
	Good	Bad
→	Bad	Good

$$\text{Recall} = \frac{|\{i : y_i = \hat{y}_i = \text{Good}\}|}{|\{i : y_i = \text{Good}\}|} = \frac{2}{3} = 0.67$$

“the fraction of the total amount of relevant instances that were actually retrieved”

# Pop Quiz #13

## Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%

# Pop Quiz #14

## Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%
- b) 50%

# Pop Quiz #15

## Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%
- b) 50%
- c) 90%

## Pop Quiz #16

### Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%
- b) 50%
- c) 90%
- d) 99%

# Pop Quiz #17

## Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%
- b) 50%
- c) 90%
- d) 99%

# Pop Quiz #18

## Quick Question!

In a dataset of 1000 samples where only 10 are positive cases, what's the accuracy of a classifier that always predicts "negative"?

- a) 1%
- b) 50%
- c) 90%
- d) 99%

**Answer:** d) 99% - but this classifier is useless! This shows why accuracy can be misleading.



# Types of Data: Imbalanced Classes

Given predictions of whether a tissue is cancerous or not ( $n = 100$ ).

Prediction ( $\hat{y}$ )

→  $\begin{pmatrix} \text{Yes} \\ \text{No} \\ \text{No} \\ \dots \\ \text{No} \end{pmatrix}$

Ground Truth ( $y$ )

→  $\begin{pmatrix} \text{No} \\ \text{No} \\ \dots \\ \text{No} \\ \text{Yes} \end{pmatrix}$

# Types of Data: Imbalanced Classes

Given predictions of whether a tissue is cancerous or not ( $n = 100$ ).

$$\rightarrow \begin{pmatrix} \text{Prediction } (\hat{y}) \\ \text{Yes} \\ \text{No} \\ \text{No} \\ \dots \\ \text{No} \end{pmatrix}$$

$$\rightarrow \begin{pmatrix} \text{Ground Truth } (y) \\ \text{No} \\ \text{No} \\ \dots \\ \text{No} \\ \text{Yes} \end{pmatrix}$$

$$\text{Accuracy} = \frac{98}{100} = 0.98$$

$$\text{Recall} = \frac{0}{1} = 0$$

$$\text{Precision} = \frac{0}{1} = 0$$

# Accuracy Metrics: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	0	1
	No	1	98

# Accuracy Metrics: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	0	1
	No	1	98

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
	No	False Negative	True Negative

# Accuracy Metric: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
	No	False Negative	True Negative

$$\text{Precision} = \frac{TP}{TP+FP}$$

# Accuracy Metric: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
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# Accuracy Metric: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
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$$\text{Recall} = \frac{TP}{TP+FN}$$

# Accuracy Metric: Confusion Matrix

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
	No	False Negative	True Negative

$$\text{Recall} = \frac{TP}{TP+FN}$$



# Accuracy Metrics: F-Score

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
	No	False Negative	True Negative

$$\text{F-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

# Accuracy Metrics: Matthew's Correlation Coefficient

		Ground Truth	
		Yes	No
Predicted	Yes	True Positive	False Positive
	No	False Negative	True Negative

$$\text{Matthew's correlation coefficient} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

# Accuracy Metrics: Example

For the data given below, calculate:

	G.T. Positive	G.T. Negative
Pred Positive	90	4
Pred Negative	1	1

Precision = ?

Recall = ?

F-Score = ?

Matthew's Coeff. = ?

# Accuracy Metrics: Answer

For the same data

	G.T. Positive	G.T. Negative
Pred Positive	90	4
Pred Negative	1	1

$$\text{Precision} = \frac{90}{94}$$

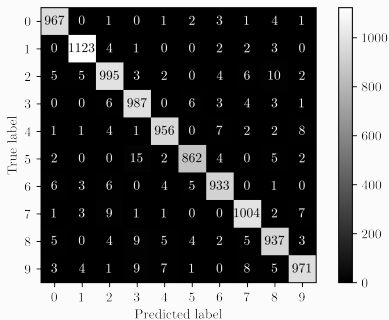
$$\text{Recall} = \frac{90}{91}$$

$$\text{F-Score} = 0.9524$$

$$\text{Matthew's Coeff.} = 0.14$$

# Confusion Matrix for multi-class classification

**Notebook:** confusion-mnist.html



# Pop Quiz #19

## Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller

## Pop Quiz #20

### Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller
- b) MAE is less sensitive to outliers

# Pop Quiz #21

## Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller
- b) MAE is less sensitive to outliers
- c) MAE is easier to compute



## Pop Quiz #22

### Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller
- b) MAE is less sensitive to outliers
- c) MAE is easier to compute
- d) MAE works only for classification

# Pop Quiz #23

## Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller
- b) MAE is less sensitive to outliers
- c) MAE is easier to compute
- d) MAE works only for classification

## Pop Quiz #24

### Quick Question!

Why might Mean Absolute Error (MAE) be preferred over Mean Squared Error (MSE)?

- a) MAE is always smaller
- b) MAE is less sensitive to outliers
- c) MAE is easier to compute
- d) MAE works only for classification

**Answer:** b) MAE is less sensitive to outliers since it doesn't square the errors!

# Metrics for Regression: MSE & MAE

Prediction ( $\hat{y}$ )	Ground Truth ( $y$ )
10	20
20	30
30	40
40	50
50	60

$$\text{Mean Squared Error (MSE)} = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\text{MSE}}$$

# Accuracy Metrics: MAE & ME

Prediction ( $\hat{y}$ )	Ground Truth
10	20
20	30
30	40
40	50
50	60

$$\text{Mean Absolute Error (MAE)} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n}$$

$$\text{Mean Error} = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n}$$

# Accuracy Metrics: MAE & ME

Prediction ( $\hat{y}$ )	Ground Truth
10	20
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$$\text{Mean Absolute Error (MAE)} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n}$$

$$\text{Mean Error} = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n}$$

Is there any downside with using mean error?

# Accuracy Metrics: MAE & ME

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10	20
20	30
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40	50
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$$\text{Mean Absolute Error (MAE)} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n}$$

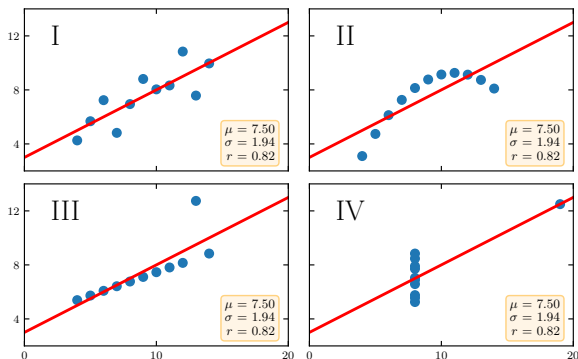
$$\text{Mean Error} = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n}$$

Is there any downside with using mean error?

Errors can get cancelled out

# The Importance of Plotting

**Notebook:** [anscombe.html](#)



Anscombe's Quartet



# Dummy Baselines

**Notebook:** dummy-baselines.html

# The Importance of Plotting

Property	Value	Across datasets
mean(X)	9	exact
mean(Y)	7.5	up to 3 decimal places
Linear regression line	$y = 3.00 + 0.500x$	up to 2 decimal places

## Pop Quiz #25

### Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision

# Pop Quiz #26

## Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision
- b) Only recall

## Pop Quiz #27

### Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision
- b) Only recall
- c) Precision, recall, and F1-score

## Pop Quiz #28

### Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision
- b) Only recall
- c) Precision, recall, and F1-score
- d) Only confusion matrix

# Pop Quiz #29

## Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision
- b) Only recall
- c) Precision, recall, and F1-score
- d) Only confusion matrix

## Pop Quiz #30

### Final Challenge!

For imbalanced datasets, which metrics should you prioritize over accuracy?

- a) Only precision
- b) Only recall
- c) Precision, recall, and F1-score
- d) Only confusion matrix

**Answer:** c) Precision, recall, and F1-score give a more complete picture!



# Key Takeaways

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- **Visualization is crucial:** Always plot your data (Anscombe's Quartet lesson)

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- **Visualization is crucial:** Always plot your data (Anscombe's Quartet lesson)
- **Use baselines:** Simple baseline models help validate your approach

# Summary: Evaluation Metrics

Task	Common Metrics	When to Use
<b>Classification</b>	Accuracy, Precision, Recall, F1 Confusion Matrix	Balanced/Imb Multi-class pr
<b>Regression</b>	MSE, RMSE, MAE Mean Error	Continuous p Check for bia

**Remember:** Choose metrics based on your problem's characteristics and business requirements!